Matching in Regular Bipartite Graphs

- ▶ For any positive integers n and d, let $\mathcal{G}_{n,d}$ denote the set of all d-regular bipartite graphs (U, V, E) where |U| = |V| = n and $E \subseteq U \times V$
- ▶ Using Hall's theorem, it is easy to argue that any bipartite graph in $\mathcal{G}_{n,d}$ admits a perfect matching
 - ► Indeed, the edge set can be partitioned into *d* perfect matchings
- We will present a fast randomized algorithm for computing a perfect matching in a given bipartite graph in $\mathcal{G}_{n,d}$

High-Level Description of the Algorithm

- Recall the elementary flow-based approach to computing a maximum cardinality matching of an arbitrary bipartite graph
 - Repeatedly augment a 0-1 flow by one unit
 - \blacktriangleright A 0-1 flow of value ℓ corresponds to a matching of cardinality ℓ
 - For a d-regular bipartite graph, the running time is O(dn) per iteration for an overall running time of $O(dn^2)$
- Our plan is to use a random walk to find an augmenting path
 - ▶ If k vertices on each side remain unmatched, we will show that the expected time for the random walk to find an augmenting path is O(n/k)
 - ▶ This results in an overall expected running time of $O(n \log n)$

Analysis of a Single Augmentation: Basic Definitions

- Assume that our bipartite graph G = (U, V, E) belongs to $\mathcal{G}_{n,d}$
- Let U_0 (resp., U_1) denote the unmatched (resp., matched) vertices in U
- Let V_0 (resp., V_1) denote the unmatched (resp., matched) vertices in V
- Let μ denote the current matching
 - For any vertex u in U_1 , we write $\mu(u)$ to denote the match of u in V_1
 - For any vertex v in V_1 , we write $\mu(v)$ to denote the match of v in U_1



The Random Walk

- ▶ Instead of introducing a source and sink, we will start at a uniformly random node in U_0 , and we will terminate once we reach any node in V_0
 - From a node u in U_0 , we go to a uniformly random node in $\Gamma(u)$
 - From a node u in U_1 , we go to a uniformly random node in $\Gamma(u) \mu(u)$
 - From a node v in V_1 , we go to $\mu(v)$
- \blacktriangleright We can easily prune the random walk walk to obtain a simple alternating path for augmenting the matching μ
- For any node x, let b(x) denote the expected number of "back" edges (i.e., edges from V to U) traversed before the walk terminates, assuming that we are currently at node x



Analysis

▶ Lemma 1: For any v in V, we have

$$b(v) = egin{cases} 0 & ext{if } v \in V_0 \ 1 + b(\mu(v)) & ext{if } v \in V_1 \end{cases}$$

- If v belongs to V_0 then the walk terminates
- If v belongs to V_1 then we traverse the back edge from v to $\mu(v)$, and the walk continues from $\mu(v)$

▶ Lemma 2: For any u in U_0 , we have

$$d \cdot b(u) = \sum_{v \in \Gamma(u)} b(v)$$

- From a vertex u in U_0 , we select a uniformly random vertex v in $\Gamma(u)$, traverse the "forward" edge from u to v, and then continue the walk from v
- ▶ Hence b(u) is equal to $\frac{1}{d} \sum_{v \in \Gamma(u)} b(v)$



▶ Lemma 3: For any u in U_1 , we have

$$d \cdot b(u) = -1 + \sum_{v \in \Gamma(u)} b(v)$$

- From a vertex u in U_1 , we select a uniformly random vertex v in $\Gamma(u) \mu(u)$, traverse the "forward" edge from u to v, and then continue the walk from $\mu(v)$
- ▶ Hence b(u) is equal to $[-b(\mu(u)) + \sum_{v \in \Gamma(u)} b(v)]/(d-1)$
- ► Equivalently, $(d-1)b(u) = -b(\mu(u)) + \sum_{v \in \Gamma(u)} b(v)$
- ▶ The claim follows since $b(\mu(u)) = 1 + b(u)$

- ▶ Lemma 4: $d \sum_{u \in U} b(u) = (d-1)|\mu| + d \sum_{u \in U_1} b(u)$
 - ▶ By Lemmas 2 and 3, the LHS is equal to $-|\mu| + \sum_{u \in U} \sum_{v \in \Gamma(u)} b(v)$
 - Since the graph is d-regular, this is equal to $-|\mu| + d \sum_{v \in V} b(v)$
 - ▶ By Lemma 1, this is equal to $-|\mu| + d(|\mu| + \sum_{u \in U_1} b(u))$
 - ► The claim follows



- Let T_k denote the expected length of the random walk when $|U_0| = |V_0| = k$ and hence $|\mu| = n k$
- ▶ Thus $T_k = 1 + \frac{2}{k} \sum_{u \in U_0} b(u)$
- ▶ Lemma 4 implies that $d \sum_{u \in U_0} b(u) = (d-1)(n-k)$
- ► Hence $T_k = 1 + \frac{2(d-1)(n-k)}{dk} < 1 + 2n/k$
- Thus the overall expected running time is

$$O\left(\sum_{1\leq k\leq n}T_k\right)=O(nH_n)=O(n\log n)$$



How Robust is this Result?

- ▶ Intuitively, one might expect the $O(n \log n)$ expected time bound to hold for graphs that are "nearly" regular (and contain a perfect matching, say)
- Somewhat surprisingly, even a small deviation from regularity can dramatically worsen the expected running time
- We will demonstrate a bad example where we add a single additional edge to a 3-regular bipartite graph
- We begin by discussing a random walk on a cycle

A Random Walk on a Cycle

- ▶ Consider a cycle with n nodes indexed from 0 to n-1 in clockwise order
- Consider a random walk starting at node i
 - At each step of the walk, we use an independent fair coin flip to determine whether to move one step clockwise or one step counterclockwise
 - The walk ends when we reach node 0
 - It is not hard to prove that the expected number of steps is i(n-i)
 - ▶ Thus if we start at $\Theta(n)$ distance from node 0, the expected running time is $\Theta(n^2)$

A Random Walk on a Cycle (cont'd)

- ▶ Suppose that we start the random walk at a node $i \neq 0$
- ▶ Let *E* denote the event that the random walk terminates by moving from node 1 to node 0
- ▶ Thus $\neg E$ is the event that the random walk terminates by moving from node n-1 to node 0
- ▶ It is not hard to prove that Pr(E) = (n i)/n

A Bad Example

- Let *n* be an even positive integer, and consider the following bipartite graph G = (U, V, E) in $G_{n,3}$
 - ▶ Index the nodes in U (resp. V) from 0 to n-1
 - ▶ Connect each node i in U to nodes (i-1) mod n, i, and (i+1) mod n in V
- ▶ Construct G' = (U, V, E') from G by setting E' to E + (u, v) where u is the node with index 0 in U and v is node the node with index n/2 in V
- Assume that our current matching μ matches node i in U to node i in V for $1 \le i \le n$
- ▶ What is the expected running time of the random walk in *G'* that starts at the node with index 0 in *U* and terminates at the node with index 0 in *V*?



A Bad Example (cont'd)

- ▶ Starting at the node with index 0 in U, there is a 1/4 chance that we move to the node with index n/2 in V in the first step
- If we do this, then based on our discussion of the random walk on a cycle, the expected number of steps to reach the node with index 0 in V is $\Omega(n^2)$

A "High Probability" Result?

- Let us define "with high probability" to mean "with arbitrary inverse polynomial failure probability"
- ▶ Does the random walk algorithm have $O(n \log n)$ running time with high probability?
- ► Consider the 3-regular graph *G* associated with the previous construction
- ▶ Based on our discussion of the random walk on a cycle, there is an $\Omega(1/n)$ chance that the random walk on G will reach the node with index n/2 in V
- ▶ Thus the augmentation takes $\Theta(n^2)$ time with probability $\Omega(1/n)$



An "Abort-and-Restart" Variant

- ► A natural variant of the random walk algorithm does achieve $O(n \log n)$ time with high probability
 - ► Suppose $|U_0| = |V_0| = k$
 - Recall that the expected length of the random walk is less than 1 + 2n/k
 - Markov's inequality implies that the random walk terminates within 2(1 + 2n/k) steps with probability at least 1/2
 - If the random walk fails to terminate within 2(1+2n/k) steps, we restart it from the beginning

Analysis of the Abort-and-Restart Variant

- ▶ We claim that the overall running time of the abort-and-restart variant of the random walk algorithm is O(n log n) with high probability
- ▶ To establish this, we instead analyze a related game
 - It is straightforward to verify that the bound we establish for the game implies the claim

The Game

- A video game has $\log_2 n$ "levels" indexed from 1 to $\log_2 n$, where n is a power of 2
- ► You start play at level 1 with "energy" cn log₂ n and repeatedly fight against one monster at a time
- ► Each time you fight with a monster on any level, you have a fifty percent chance of defeating the monster
- ▶ To advance from level ℓ to level $\ell+1$, you need to defeat $n2^{-\ell}$ level- ℓ monsters
- ▶ Whenever you fight with a level- ℓ monster, your energy is reduced by 2^{ℓ} , whether or not you defeat the monster
- You win if you complete all of the levels without running out of energy



Analysis of the Game

- ▶ The expected number of level- ℓ monsters faced is $2n2^{-\ell}$
- ▶ By Markov's inequality, the probability that you need to fight more than $4n2^{-\ell}$ level- ℓ monsters is at most $\frac{1}{2}$
- ▶ The cost of facing $4n2^{-\ell}$ level- ℓ monsters is 4n
- ► Let the random variable *Z* denote the number of independent flips of a fair coin required to get log₂ *n* heads
- ▶ Observe that the probability you lose the game is upper bounded by the probability that $4nZ \ge cn\log_2 n$, i.e., that $Z \ge (c/4)\log_2 n$

Analysis of the Game (cont'd)

- ▶ The probability that Z exceeds $(c/4)\log_2 n$ is equal to the probability that we get fewer than $\log_2 n$ heads in $(c/4)\log_2 n$ independent flips of a fair coin
- ▶ Recall that for a random variable X drawn from B(k, 1/2) and any δ in [0, 1], we have

$$\Pr(X \le (1 - \delta)k/2) \le \exp(-\delta^2 k/2)$$

- ▶ Using the above bound, the probability Z exceeds $(c/4)\log_2 n$ is upper bounded by an inverse polynomial in n where the exponent is quadratic in c
- ▶ Thus the probability you lose the game is upper bounded by an arbitrary inverse polynomial for a sufficiently large choice of the constant *c*

